Wavelet-lag regression analysis of Atlantic tropical cyclones and snow cover and their dependence on ENSO and Atlantic thermohaline variability.

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Abstract We discuss a novel wavelet-lag coherence method to study of cause-and-effect relations over a large space of timescales, phase lags and periods. We use 135 years of observational records to demonstrate how sea-surface temperature, sea-level pressure and cyclone numbers are linked. We examine the statistical properties of the time series and test how departure from Normality affects results found using the method. We also examine how historical inaccuracy in counting tropical cyclone numbers could influence the findings. Robustly we find that SST and cyclones in a negative feedback loop, where rising SST causes increased numbers of cyclones, which reduce SST. This is statistically most significant at decadal and not at longer periods. Only at periods of about 30 years do significant differences arise in using recently proposed corrections to cyclone numbers, and forcing the empirical distribution of cyclone numbers to be Normal. This could be incorrectly interpreted as support for a long period Atlantic Multidecadal Oscillation, whereas it actually reflects the time-varying bias functions applied to the observations. There is evidence of some linkage between Northern hemisphere snow cover and cyclone numbers, however this seems to be due to a common causative relationship between the known tropical cyclone

drivers of ENSO and decadal scale North Atlantic ocean-atmospheric circulation systems.

1 Introduction

Increases in Atlantic tropical cyclone intensity have been related to increases in Atlantic sea surface temperature (SST), and Elsner (2007) has shown that it is likely to be rising global temperatures that drive the increases in both cyclone intensity and Atlantic SST. However, the nature of the climate relationships to tropical cyclones is likely to be complex, and certainly includes oceanic and atmospheric circulation patterns that operate on ocean basic scales. Significant but weak statistical correlations exist between the Atlantic hurricane source region and the northern Atlantic (Goldenberg et al 2001) and tropical Pacific warm pools (Wang et al. 2006). Several authors have used these statistical relationships to produce predictive models of Atlantic hurricane season intensity and tropical storm numbers (e.g. Elsner and Jagger, 2006; Sabbatelli and Mann, 2007). In contrast with this kind of approach, here we attempt to understand relationships between the large scale driving mechanisms and Atlantic tropical storm activity by examining the behaviour of the various multi-year cycles that exist in the time series. Decadal cycles are fairly ubiquitous across the planet, and are therefore persuasive of a global-scale climate mechanism (Jevrejeva, Moore and Grinsted, 2004; Moron, Vautard and Ghil 1998; Dijkstra and Ghil 2005). The main features of the planet's climate are the ENSO and the polar annular modes, which is determined by the strength of the polar stratospheric vortex (Thompson and Wallace 1998). An index of Atlantic climate variability that is often (but not always – Jevrejeva and Moore 2001) closely related to the arctic annual mode (the Arctic Oscillation) is the North Atlantic Oscillation (NAO). Unlike the purely polar defined annular modes, the NAO is linked to the tropics via its interaction with the Atlantic thermohaline circulation, most particularly through the modulation of the Gulf Stream meanderings at 7.8 year periods (Dijkstra and Ghil 2005). This is significant as Elsner, Kara and Owens

(1999), noticed a 7.8 year periodicity in hurricane frequency.

Moore, Grinsted and Jevrejeva (2008) showed that robust linkages that may imply causal relationships between global sea-surface temperature (SST), pressure fields and cyclones exist. However, challenging the identification of such linkages are both the uncertainties in long-term observational records and the robustness of the advanced statistical methods designed specifically to extract possibly causal relationships that may be non-stationary and develop over many years. Here we examine how the results from wavelet lag regression are to perturbation of 135-year observational record and demonstrate cyclone numbers are linked on different time scales with high latitude processes that also determine snow cover in the Northern Hemisphere.

2 Data

In contrast with modern satellite-era observations of hurricane wind speeds and atmospheric physical variables, numbers of Atlantic tropical cyclones per year (TC), has been collected since at least 1851. They are defined simply as non-frontal, synoptic-scale cyclones over tropical or subtropical waters (Jarvinen, Neumann, and Davis, 2005). TC representing cyclone count and Power Dissipation Index (PDI) (Emanuel 2005; Landsea 2005), an index of hurricane destructive power available from 1944-2004 are correlated at 0.68. Recent modifications to TC have been suggested (Landsea (2007; Mann et al., 2007), however testing our results with the proposed time-varying bias added to TC makes only very slight differences to our results. For example the correlation coefficient between PDI and TC changes from 0.68 to 0.69. While Landsea (2007) makes good arguments for the systematic undercounting of tropical cyclones in the past due to the their existence being unnoticed, Mann et al., (2007) suggest various difficulties with a simple correction under the assumption of stationary climate forcing, and point out that sparse observations can also lead to over-counting when a single event is counted as two or more events. Moore, Grinsted and Jevrejeva, (2008) showed the correlation between PDI and TC has varied over time, but for much of the common period of data the correlation is significant at the 95% level; with only the period prior to 1955 showing consistently lower significance. Moore, Grinsted and Jevrejeva (2008) concluded that as the moving correlation between TC and PDI (Fig. 1) was generally high, that TC could be used as a surrogate with reasonable confidence. Here, however we will examine the revised TC in some detail. The long TC record allows more rigorous significance testing for long period variability than analyses that have focused on the instrumental records available only from 1940s or later (Emanuel 2005; Michaels, Knappenberger and Davis, 2006).

We consider the set of SSTs for the Atlantic averaged over the area 6-18°N, 20-60°W, defined as the cyclone main development region (MDR), during the months of August, September, and October, (SST_C). We use the HadISST2 data (Rayner et al. 2003) which extends from 1870 to 2004. There is no theory that predicts the number of Atlantic tropical storms directly as a function of SST (or potential intensity). GCM simulations suggest that there is a link between rising SST and strength of hurricane maximum wind speed, such that a 1ºC rise in SST_C leads to a 5% increase in maximum wind speed (Knutson and Tuleya 2004). However observations in the Atlantic region suggest that the PDI, which is dominated by the largest storms, has increased by about 20% per ºC since 1980, and perhaps by 10% per ºC over the Twentieth Century (Emanuel 2005; Landsea 2005).

We used the historical variation in Northern Hemisphere and Eurasian snow cover extent derived from reconstructed daily snow depth (1922-1971) and NOAA satellite data (1972-1997). The method for reconstructing snow cover extent is described in Brown (2000). The spatial distribution of historical *in situ* data meant that reconstruction of continental-scale snow cover extent was only possible in three months: October, March and April for Eurasia, while for the whole Northern Hemisphere it was only possible for March and April. We constructed 2 indices: one of spring Northern hemisphere snow cover as the mean of march and April coverage, and one Autumn coverage for Eurasia based on the October extent in Eurasia. It is worth pointing out that these records are far longer than the purely satellite derived snow over extent data which begins only in 1972, and hence is of virtually no utility in examining decadal or longer relationships with other times series.

3 Methods

Elsner (2007) uses the method of Granger causality to determine phase relationships between time series, and finds convincing evidence for mechanistic relationships between Atlantic SSTs and global temperatures. In contrast with Granger causality methods that work in the time-domain, here we use wavelet methods. The method we use (Moore, Grinsted and Jevrejeva. 2007; Moore, Grinsted and Jevrejeva 2008) determines the non-linear interactions between the two time series that may be chaotic. Briefly we extract the phase expression of the time series derived from the Continuous Wavelet Transform (CWT) of a time series (e.g. Grinsted, Moore and Jevrejeva 2004; Torrence and Compo 1998). Here we apply broad band pass wavelet (the Paul wavelet of order 4) to filter the time series. The centre frequency of the Paul wavelet, λ, is an important parameter in the analysis.

The wavelet is stretched in time by varying its scale (s), so that $\eta = s \cdot t$, and normalizing it to have unit energy. The CWT of a time series X, $\{x_n, n=1,\ldots,N\}$ with uniform time steps δt, is defined as the convolution of x_n with the scaled and normalized wavelet.

$$W_X(s,t)\big|_{t=n} = \sqrt{\tfrac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'} \psi_0 \left[(n'-n) \tfrac{\delta t}{s} \right].$$

The complex argument of $W_X(s,t)$ can be interpreted as the instantaneous phases of $X\{\varphi_1\ldots, \varphi_N\}$ at the scale s. We utilize the strength of the instantaneous phase angle difference between two series (X and Y), also known as the mean phase coherence, $\rho(X,Y)$ (Mokhov and Smirnov 2006). We are interested in causative relations, so it is appropriate to measure ρ between the instantaneous phases φ and θ of the two time series

$$\rho = \frac{1}{N} \sqrt{ \left(\sum_{t=1}^{N} \cos(\phi_t - \theta_t) \right)^2 + \left(\sum_{t=1}^{N} \sin(\phi_t - \theta_t) \right)^2 }$$

We vary the relative phase delay between the two series by lagging φ relative to θ by a phase lag, Δ. Significance testing of ρ is done by Monte Carlo methods against 1000 realizations of a red noise background (Grinsted, Moore and Jevrejeva, 2004), and the results can be visualized in a two-dimensional plot of ρ in λ-Δ space analogous to the wavelet frequency-time space plot. As a further refinement in the utility of such a plot we find it useful to contour the strength of linear regression of the wavelet filtered time series as a function of λ and Δ, so that the color scale bar corresponds to the value of *m* in the equation of $W_Y(\lambda,t+\Delta) = m\, W_X(\lambda,t)$. The phase relationship over the range multi-year to decadal periods was examined by filtering both time series with a Paul wavelet with λ between the Nyquist frequency and 40 years with six λ per octave of scale.

4. Results

4.1. TC corrections and Normality

It is well known that the TC time series is not Normally distributed but follows a Poisson distribution (Solow and Moore, 2000). However here we are interested to see how the non-Normality affects the novel statistical techniques we use. There is also a question as to how discrete data such as TC can be used in methods that were developed for continuously distributed data. One approach to providing a more continuous time series could be smoothing by running averaging the TC rate over a variety of scales, though any particular length of the running average would create data that would still be rational numbers. The smoothing window would naturally tend to produce a more Normal distribution via the Central Limit Theory. The CWT method is superior to running means as it effectively smoothes the data by the particular wavelet filter used, and this creates a much less discreet set of data. For both the modified and raw TC time series a Bera-Jarque test of Normality is rejected (p=0.02) Fig. 2), however, the data are acceptably Lognormal (p=0.15). Clearly this is due to the TC being non-negative with a long tail.

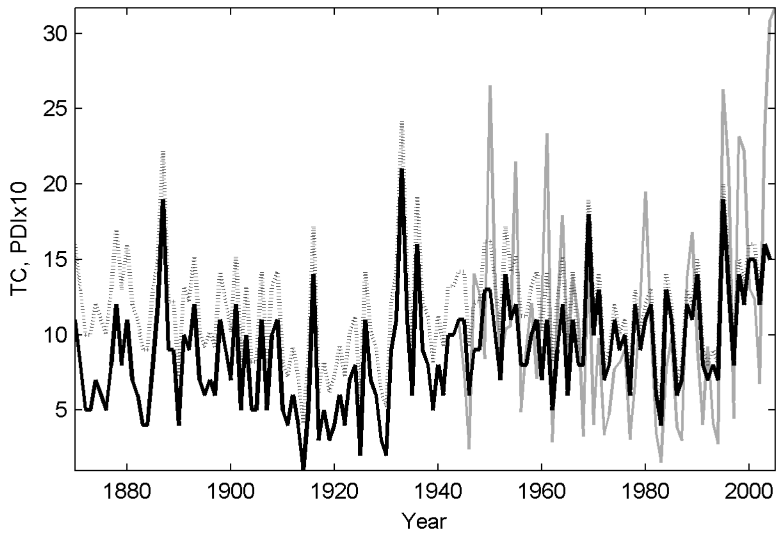

Fig. 1. Time series of TC (black), modified TC (grey dotted) and PDI (grey, multiplied by 10).

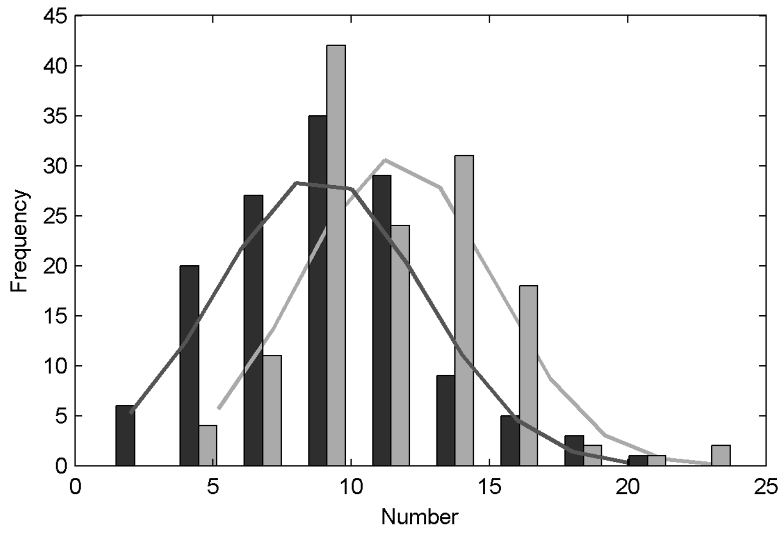

Fig. 2. Distribution of TC (black) and modified TC (grey), and their best fit Normal distributions**.**

We can remove the lack of Normality from the TC distribution completely by making use of a Normalization procedure (Jevrejeva, Moore and Grinsted, 2003). We transform the original data using a data adaptive transformation function. The transformation operator is optimally chosen so that the new probability density function is Normal, has zero mean and unit variance. This is calculated by making the inverse normal cumulative distribution function of the percentile distribution of the original distribution (Fig. 3). We refer to this procedure as Normalization and it can be a rather drastic operation to use on a time series. However, Jevrejeva, Moore and Grinsted, (2003) have shown that the results from even grossly non-Normal distributions, that would not produce reliable results with the wavelet method, do give results after Normalization that are consistent with alternative methods of signal extraction such as Singular Spectrum Analysis. Henceforth we denote the Normalized modified TC series as TC"

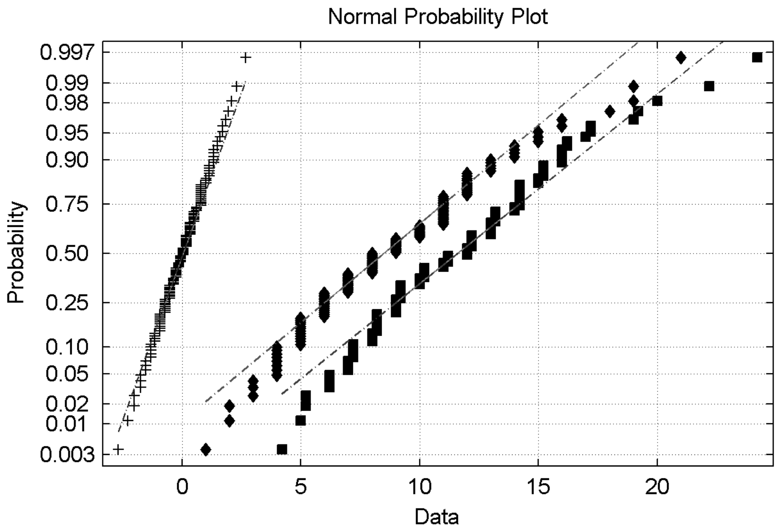

Fig. 3. The raw TC data (diamonds), (from Mann et al., 2007) modified TC (squares), (from Landsea, 2007) and Normalized modified TC (TC") (marked by +) created as described in the text, plotted on normal probability scaling so that straight lines represent a Normal probability distribution.

Fig. 4 shows at first glance, quite large differences in significant regions. However, the differences in the actual values of coherence are rather slight, the coherence being quite close to the 95% value that marks the border. There are quite small differences in the time derivative $dSST_C$ plots. The differences become smaller if the simple normalized times series or the simple modified time series are compared with the original TC. The largest differences are in the 25-30 year band, with no significant region in the raw TC curve but a quite large region in the normalized modified TC data. Again at first glance this may seem to offer support for the low frequency AMO oscillation, but there should be a number of cautions. The largest region of significance is in the rather dubious physical region of the graph whereby TC determines SST_C at rather long lead times of a decade or more.

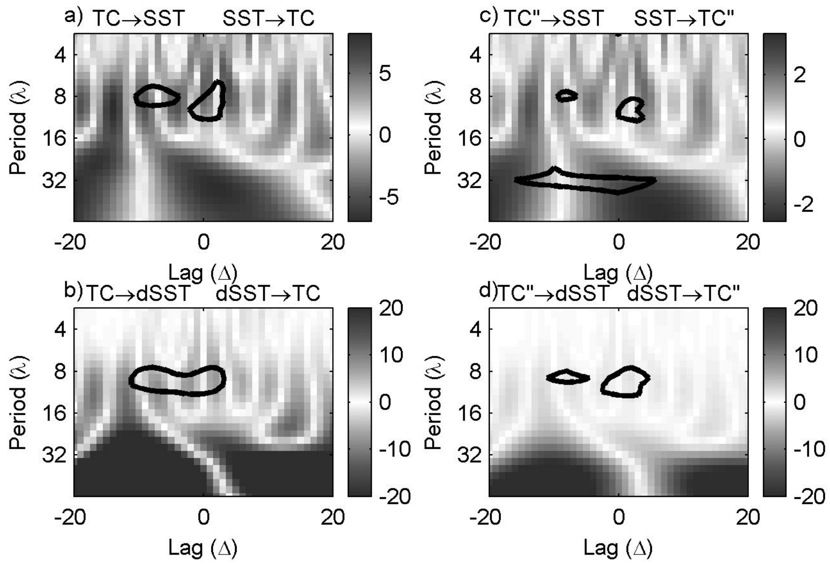

Fig. 4. Wavelet lag coherence plots showing: (a) TC sensitivity on SST_C ($W_Y(\lambda,t+\Delta) = m\, W_X(\lambda,t)$, *m* in number per °C is shown on the colour bar, as a function of Paul wavelet filtered period (λ) and phase lag (Δ), solid black contour is 95% confidence interval of mean phase coherence (ρ) contours The arrow notation in Y→X etc. denotes that Y leads X in lag space. (b) TC and the d SST_C. (c) Normalized modified TC (TC”) and SST_C and (d) TC” and the d SST_C

An alternative complimentary method of examining the data is using wavelet coherence. Fig. 5 shows that there are very slight differences between the TC” Normalized modified TC time series and the raw TC series.

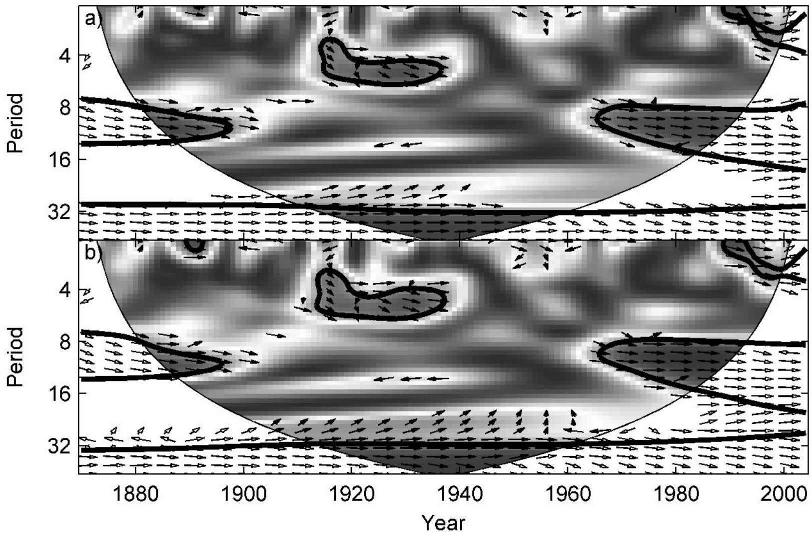

Fig. 5. (a) Squared wavelet coherence between SST_C and TC (dark high values, light low values). The 5% significance level against red noise is shown as a thick contour. The relative phase relationship is shown as arrows (with in-phase pointing right, anti-phase pointing left, and SST_C leading TC by 90º pointing straight down), the curved lines with no colouring delineate the region affected by data boundaries (Grinsted, Moore and Jevejeva, 2004); (b) As for (a) but with the Normalized modified TC and SST_C.

4.2. Snow cover and Cyclones

It has been suggested that the large scale atmosphere is impacted by cyclone activity for some considerable period after the cyclone has dies away. This memory may be expected to manifest itself on seasonal snow cover in the Northern Hemisphere. We investigate this using the long series of snow cover estimates from Brown (2000). Fig. 6 and 7 show the behaviour of Northern Hemisphere spring snow coherence and sensitivity with TC and TC”. Perhaps most surprising is that Fig. 6 shows that the relationship is basically in-phase, so that more spring snow implies greater numbers of TC. However, Fig. 7 shows that the relationship is not significant except at rather long positive and negative lags of about a decade. Particular mechanisms for interactions with snow cover have been proposed by Hart, Maue and Watson (2007). In particular they suggest that autumnal snow cover may be influenced by TC. Fig. 8 and 9 examine October snow cover extent 1922-1997 in Eurasia – time series for the whole Northern Hemisphere not being available. In contrast with Figs. 6 and 7, we see that the relationship is consistently anti-phase, with zero or small lag times, but significant only at decadal periods. Thus we see that the spring and autumn snow covers react in quite different ways. We also tested the Eurasian spring snow cover relationship with TC (not shown here) and found the wavelet coherence to be very similar as for the Northern Hemisphere as a whole (see Fig. 6), but the lag coherence had no areas of significance.

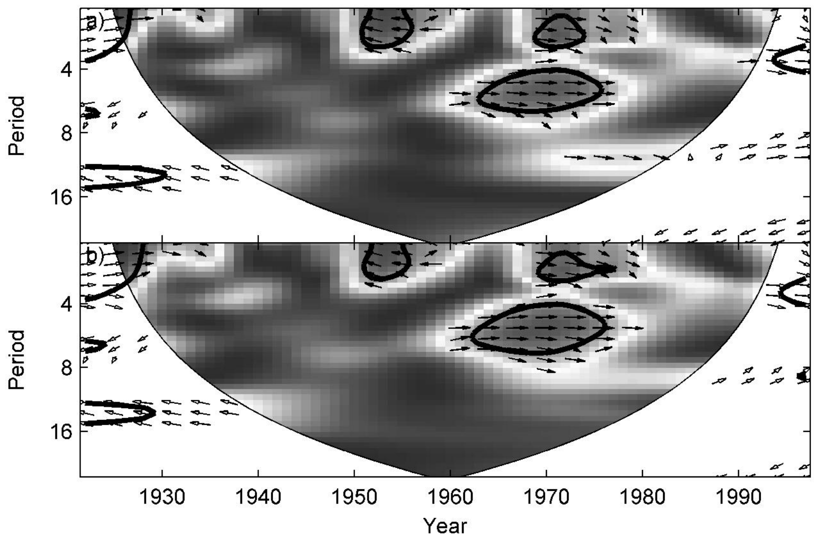

Fig. 6. (a) Squared wavelet coherence between Northern Hemisphere spring snow cover and TC. Contours and arrows as for fig. 5. (b) coherence between Northern Hemisphere spring snow and TC" .

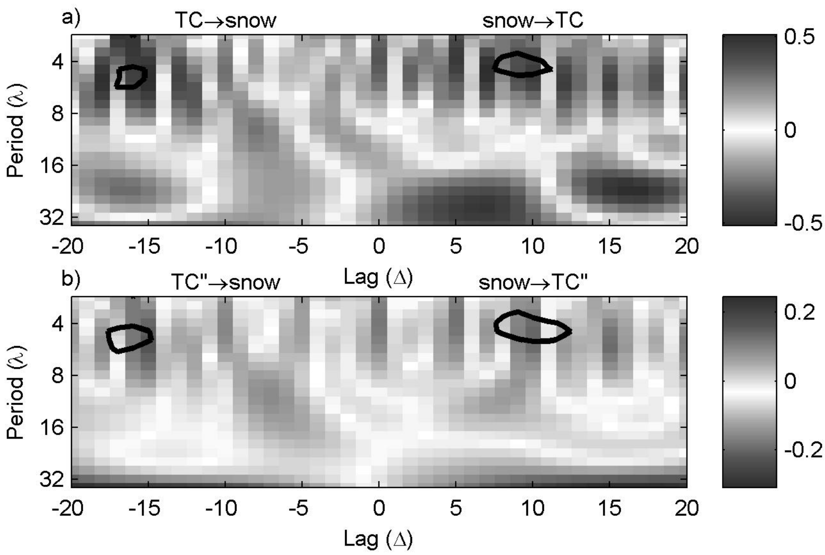

Fig. 7. (a) sensitivity of TC on Northern Hemisphere spring snow and (b) sensitivity of TC" on Northern Hemisphere spring snow. Contours and color bars as fig. 4.

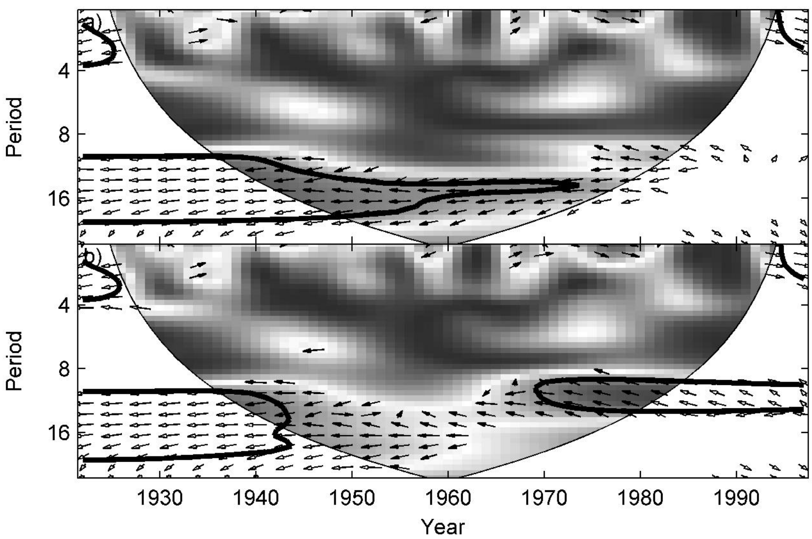

Fig. 8. As for fig. 5 but (a) TC and Eurasian autumn snow and (b) TC" and Eurasian autumn snow.

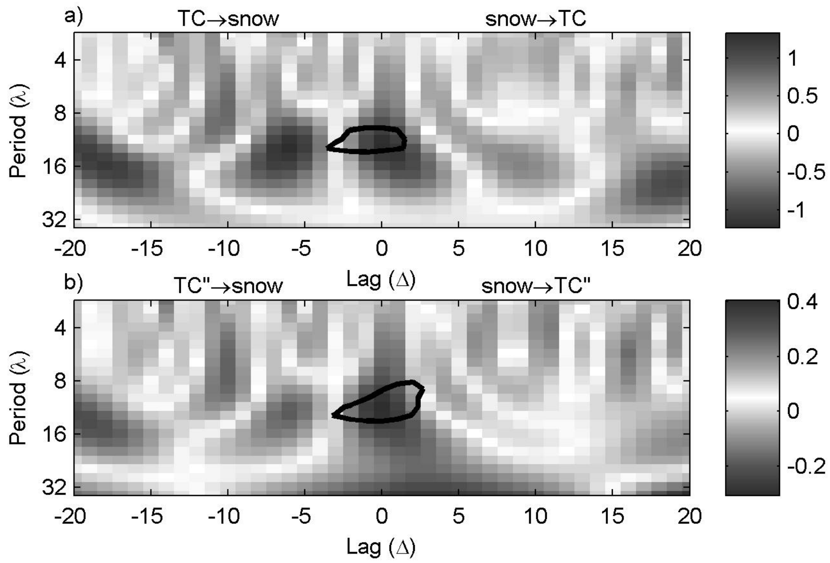

Fig. 9. As for Fig. 4 but (a) TC and Eurasian autumn snow and (b) TC” and Eurasian autumn snow.

5. Discussion and conclusions

5.1. TC time series and statistical testing

It has already been argued (Mann et al., 2007) that the modifications suggested by Landsea (2007) and others, do not affect the main results of trend and correlation analysis between SST_C and TC. We show quite clearly that this is also true of analysis of the coherence and lag regressions of the modified time series, which even largely survive the gross manipulation of the time series to ensure complete Normality. One reason why the wavelet methods we use are not particular sensitive to the actual distribution of the data is that the Paul – and indeed most if not all wavelets, use more data points in their filter than required by simple Nyqust frequency considerations. This means that we smooth the data by a series of filters of different lengths. While the wavelet filters are infinitely long, the minimum scale used here is 2 which for the Paul wavelet of order 4 corresponds to a shortest period of about 2.8 years for annual data. The longer the filter, the more smoothed the data and the closer the distribution of data within that sample length will be to Normally distributed by the Central Limit Theory.

It has been suggested that our significance tests done on the wavelet data may be misinterpreted. That is small areas of significance at the 95% level could occur purely randomly some of the time, and so if the significant region is a small part of the whole figure, it may be there purely by chance. However this does not take into account that the tests are on phase relationships not measures of common power. Hence the significance will not be inflated simply by a few common bits of high power in the two series. This is borne out by testing of many series where we find absolutely no region of significant coherence regardless of how large the plot is made in lag-period space. The significance test uses the most conservative red noise model available, i.e. matching the original series mean, standard deviation and lag-1 autocorrelation, so the Monte Carlo common coherence thresholds found will be more conservative than simply random noise would give. This follows as red-noise that does not possess the same characteristics as the data would be less correlated with the data and hence provide a lower significance threshold in Monte Carlo testing than given by noise matching the data characteristics. However, since the procedure is essentially band pass filtering, the type of noise distribution is not very critical for significance testing. Similarly as the coherence is a phase matching rather than common power finding method, the relative power distribution is not important in frequency space. Therefore the actual noise model e.g. red noise auto regressive (AR1) or fractional Gaussian (self-similar scaling), is less important for significance testing than would be case for many other statistical methods.

5.2 TC interaction with snow cover

The results presented in Figs. 6-9 are rather curious. The differences between spring and autumn snow cover are somewhat suggestive of the differences seen at 5 year and decadal periods in TC and SST_c which Moore, Grinsted and Jevrejeva (2008) interpreted by ENSO and Gulf Stream /NAO variability. The decadal power seen in autumn snow is consistent with the ideas suggested by Hart, Maue and Watson, 2007 regarding the extra-tropical impact of tropical cyclones. The larger the number of tropical cyclones, the less autumn snow cover appears to be logical given the energy transport from tropics mediated by the cyclones. The surprising feature is that this effect is only apparent at decadal periods. This suggests a common causal factor with SST_c decadal variability (Fig. 4 and 5) ascribed to NAO/Gulf Stream variability at 7.8 years. NAO phase is known to strongly impact precipitation in Europe and the Middle East, so this observation is consistent with ideas that NAO plays a useful role in predicting TC. Positive NAO phase has been related to decreased sea level pressures (SLP) over the Arctic region - with a minimum over Iceland- and a northeastward extension of the Atlantic storm track to Greenland, Iceland, Norway and Barents Seas, causing major increases in cyclone activity in the area and thus increased heat flux over the region (Serreze et al. 1997; Alexandersson et al. 1998). Such situations enhance southerly warm winds over the western Nordic Seas, causing 1) compaction and reduced freezing in the ice margin (Vinje 2001), 2) warm air advection (Deser, Walsh and Timlin, 2000), and 3) enhanced flow of warm and saline Atlantic water (Grotefendt et al. 1998; Morison, Aagaard and Steele, 2000; Polyakov et al. 2004). Persistent positive NAO phase is predicted by climate models as a consequence of global warming (e.g. Gillett, Graf, and Osborn, 2003). Regardless of this, NAO relationships with Arctic environment are far from stationary. Surface air temperatures (SAT), SST, and SLP over the North Atlantic during the period 1873-2000 have alternated decades of strong negative with decades of strong positive correlations with NAO (Polyakova et al. 2006). Likewise, NAO and SAT records from Europe showed significant non-stationarities on decadal time-scales (Slonosky, Jones and Davies 2001). Suggested mechanisms for such non-stationarities are the co-occurrence or otherwise of several NAO-related SLP patterns (Maslanik et al., 2007), or the planetary-scale SLP wave (Cavalieri, 2002).

The spring snow cover – in the northern hemisphere, but not in Eurasia, has significant common coherence with TC in the 5 year band. If this is an ENSO feature then it is entirely plausible given the impact of ENSO on the Pacific Decadal Oscillation (PDO) and the observed large impact that the PDO has on North American climate (Biondi, Gershunov, and Cayan, 2001). The long lags seen (Fig. 7) may in fact be a reflection of the dominant bi-decadal periodicity of the PDO (Minobe, 1999) on the fundamental ENSO impact on TC that has been observed for many years (Gray, 1984; Moore Grinsted and Jevrejeva (2008).

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